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Research Article

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Posted Date: October 12th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-953021/v1>

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Modelling Wetland Eco-hydrological state in Pressure-State-Response framework validating it using Ecosystem service potentiality approach

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Abstract

The present study has tried to model the Eco-hydrological state of wetlands for both pre dam and post dam periods of the Lower Tangon river basin using Pressure-State-Response (PSR) framework with advanced machine learning (ML) algorithms and validated it with Ecosystem service potentiality (ESP) approach along with conventional approaches of validation. All the applied models have explored that 22.48% to 39.52% wetland under very good EHS zone has converted into 15.52% to 16.57% relatively lower category of EHS zones indicating the gradual degradation of EHS quality over wider parts of the wetland. The result of model validation has noted the acceptability of all the applied models but performance is found high in the case of REPTree and Bagging models. Expert-based ESP behaves accordingly with the EHS models. Based on the results, the study suggests using ML models for such modelling and used field-based validation approach like ESP.

Keywords: Eco-hydrological state, Machine learning models, Pressure-State-Response, Receiver operating curve and Valuing ecosystem service potentiality

1. Introduction

Wetlands is a valuable natural resource that covers 6% of the world's geographical surface (Mitsch et al., 2010) but offers habitats for many rare species and contributes 40% of the global ecosystem services (Khatun et al., 2021). According to Ramsar Convention on Wetlands (2002) seasonal wetlands as a subset of the 'transitory pool' assigned these to the rundown of wetlands of universal importance (Ramsar, 2002). Wetland is one of the most distinct ecosystems and ecologically sensitive part of the biodiversity of the world. Wetlands provides various

provisioning services such as wood, food, fresh water, fodder, genetic materials, medicinal materials; regulating services such as global and local climate regulation, air purification, water flow regulation, waste treatment, nutrient regulation, renewal of soil fertility, pollination, soil erosion prevention, flood control; cultural services which includes recreation or tourism, landscape aesthetics, natural diversity, cultural diversity and numerous others for human well-being (Keddy et al., 2000; MA, 2005, Chen et al., 2011; Burkhard et al., 2014; Costanza et al., 2014; Luo et al., 2018; Lin et al., 2019; Pal and Sarda, 2020). Despite agreeing with the ecological significance of wetlands, their importance are consistently neglected (Turner et al., 2013). The wetlands are losing their importance because of anthropogenic pressure and negligence of human activity (Pal and Sarda, 2020). So, wetlands are the most dehumanized natural ecosystem all over the globe in recent decades (Finlayson et al., 2016) in spite of its priceless values. The global ecosystem has been faced critical threats because of global climate change, rapid urbanization, human disturbance, over exploitation of natural resources, infrastructural development, agriculture expansion etc. from the mid-twentieth century (Luo et al., 2018; Das et al., 2020). The wetlands degradation is very common phenomena in developing countries like India where population pressure is very high (Das and Basu, 2020; Pal and Talukdar, 2018; Ghosh et al., 2018). In India, many wetland ecosystems have been witnessed a rapid detracton, including deterioration in water quality, squeezing wetland area, shallowing water depth in wetland and loss of biodiversity (Talukdar and Pal, 2017; Pal and Talukdar, 2018; Das et al., 2020; Pal and Sarda, 2020; Talukdar et al., 2020a). The hydrological characteristics such as frequency of flow, discharge amount, timing, hydro-period has been changes due to artificial control like dam construction in the stream (Graf, 2006; Pal, 2016), but also modifies the hydrological regime of the riparian wetlands (Pal and Talukdar, 2020; Pal and Sarda, 2020). Due to the such modification wetlands are experiencing problems like reduction of flow, decreasing of water depth, narrowing hydro-period, uncertain water level fluctuation which is very crucial factors for sustaining ecosystem and habitat status of the river and riparian wetlands (Talukdar and Pal, 2020b; Saha and Pal, 2019; Debanshi and Pal, 2020a). All these changes invite changes in wetland ecosystem health. A good number of evaluation techniques have been developed for ecological state modelling, such as Analytical hierarchy process (AHP) (Sun et al., 2019; Li et al., 2021), driver-pressure-state-Impact-response (DPSIR) (Zhang et al., 2016), ecological footprint model (Ning et al., 2015), vigor-organization-resilience (VOR) (He et al., 2019) etc. These methods have their own limitations, some of which are very difficult to implemented, such as the ecological footprint model (Wang et al., 2018; Altintas and Kassouri, 2020). The other models are too subjective which allow

expert knowledge in determining the weights of the parameters, such as the AHP model (Ghosh et al., 2020; Pal et al., 2021). The relationship between resources and environmental impacts was properly well-established by PSR (Pressure state response) model (Neri et al., 2016; Liao et al., 2018), which was proposed by the organization for Economic Co-Operation and Development (OECD) and the United Nations Environmental Program (UNEP).

In recent times, advance remote sensing (RS) technology gained extra attention in the scientific community for accurately modelling ecosystem health, ecological environment, eco-hydrological status etc. due to its large data character, real-time database, wide geographical coverage and relatively low cost and time saving merits (Mulder et al., 2011; Liu et al., 2018). RS techniques were widely used for monitoring spatial-temporal changes of different environment (Hu and Xu, 2018).

Modeling earth and environmental processes using advanced techniques is a well-accepted approach for understanding the process precisely. In recent times, several techniques have been developed and successfully applied in various fields of environmental research, such as (i) expert-based model like AHP (Pal et al., 2021), statistical and bivariate approaches such information value (Chen et al., 2020), frequency ratio (Pal and Talukdar, 2018), certainty factor (Arabameri et al., 2019), logistic regression (Pal and Talukdar, 2018), weight-of-evidence (Arabameri et al., 2019), fuzzy logic (Basu et al., 2020), neuro fuzzy logic (Tabbussum et al., 2021); (3) machine learning algorithms such as artificial neural network (Singha et al., 2020), random forest (Wan et al., 2019), random tree, support vector machine (SVM) (Debanshi and Pal, 2020b), REPTree (Saha et al., 2020), random subspace (Talukdar et al., 2021), bagging (Talukdar et al., 2021), dagging (Islam et al., 2020), logitboost (Talukdar et al., 2021), MSP (Kumar and Deswal, 2020) etc. Recently machine learning algorithms were widely used in the environmental science and disaster management field by many researchers due to its wide application, higher accuracy and good performance. Due to this reason machine learning algorithms have drawn growing attention in different fields (Talukdar et al., 2021; Singha et al., 2020). In the field of ecology and environment researchers frequently used machine learning models for modelling habitat quality (Pal et al., 2020; Talukdar and Pal, 2019); estimating water richness zones (Pal and Sarda, 2020; Debanshi and Pal, 2020a); assessing wetland habitat vulnerability (Talukdar and Pal, 2020b), modelling eco-hydrological status (Hesse et al., 2008; Khatun et al., 2021). PSR model and application of ML models are not any novel approach but developing PSR model using multi-model ML algorithm is quite new. The present work has attempted to develop PSR model using ML approach. Statistical test such as

receiving operation characteristics (ROC), Friedman test, Wilcoxon signed rank test, root mean square error (RMSE), mean absolute error (MAE), relative absolute error (RAE) are frequently used for evaluating the performance of the machine learning models (Talukdar et al., 2021). Apart from statistical tests, the present study has performed a field based ecosystem service potentiality (ESP) analysis (Koschke et al., 2012; Tangarife et al., 2017) for validating the ML based PSR models. This approach of study is very effective and newly introduced in this present study.

The downstream segment of the Tangon river basin of Barind tract (Fig. 1) is characterized by huge population density and infrastructural development such as road networks, railway networks etc. Apart from this Boda dam was constructed in 1989 in Panchagarh district in Bangladesh for irrigation purpose over the upper part of the river basin significantly reducing water discharged level by 63% in the downstream of Tangon river. (Pal et al., 2019). This reduction of water level is caused by hydrological dynamics in riparian wetlands of this river basin, areal squeeze of the wetland by 71.71% from pre to post dam periods (Chakraborty et al., 2018). In this study area some scattered works of hydrological modification were done but no such integrated work has been done yet addressing PSR state which is a major focus of this study.

2. Materials and methodology

2.1 Study area

Tangan river, a downstream tributary of river Mohananda flows over Bangladesh and India (125 km on Bangladesh and 142 km on India) and built up a 2388.88 km² trans-boundary basin over Indo-Bangladesh barind region (1234.68 km² in Bangladesh and 1154.20 km² in India) extending from 26° 19' 56" N/88° 14' 14" E to 24° 57' 22" N/ 88° 29' 29" E. The region is dominated by subtropical monsoon types of climate having high degree seasonal variation of temperature and rainfall. The average rainfall per year of this region occurs between 1257.42 mm to 1508.05 mm (Pal et al., 2019), about 80% of which takes place in the monsoon season covering the months June to September. The topography is flat with an elevation range between 8 to 83 meters. The area mostly exhibits sandy loamy soil texture type, which is very fertile for producing a wide range of agricultural crops. Geographically this region belongs to North-Western part of Bangladesh and Eastern part of India. The population density of Bangladesh part is 728 persons/km² and India part is 665 persons/km² and about 70% people are involved in primary activities like farming, hunting, fishing etc. (Pal et al., 2020). The land use consists

of a water body, built-up area, agricultural land and vegetation, where more than 60% area is covered by agricultural land. Flood common natural hazards and almost occur in every year in the catchment due to very high intensity or short extent of monsoon rain spell. The downstream segment of the river basin experienced a reduction of river flow due to the construction of Boda barrage (Pal et al., 2019). Apart from this, cross-border issues are also experienced between India and Bangladesh in this river basin. Due to this incident, the hydrological characteristics of the lower Tangon basin and its riparian wetlands was also changed. Rainwater and river water are the main sources of water of these wetlands. Some researchers already identified the damming effects on wetlands hydrological characteristics in this river basin (Pal et al., 2019; Pal et al., 2020).

Figure.1 Location map of the study area

2.2 Database

Cloud free Landsat 4-5 (TM) and Landsat 8 (OLI) data since 1980 to 2020 with spatial resolution of 30 meter have been taken from USGS (United States Geological Survey) earth explorer websites (<https://earthexplorer.usgs.gov>) and used for wetland mapping, land surface temperature (LST) agricultural presence frequency (APF), distance from agricultural land, distance from built-up area, land use and land cover (LULC) change, Patch Density (PD), Patch Richness (PR), Patch Richness Density (PRD), Shannon's Diversity Index (SHDI), Modified Shannon's Diversity Index (MSIDI), Simpson's Evenness Index, Modified Simpson's

Evenness Index, wetland depth, range of variability (RVA), wetland fragmentation, ecosystem services value (ESV), change rate of water presence frequency (WPF) and wetland depth change mapping. Population density map has been prepared from Census population data (Census of India, 1991 and 2011). The field specific data and satellite images has been used for preparing turbidity index, Secchi disk depth (SDD), chlorophyll-a, total phosphorus mapping. Entire period of analysis has been subdivided into two phases, pre-dam (before 1989) and post-dam (after 1989) phases. Landscape Fragmentation Tool, SPSS and ArcGis (Version 10.3) software have been used for carrying out the study. Field validation methods have been applied to validate the eco-hydrological state model.

2.3 Influencing factors and preparation of the data layers

Wetland eco-hydrological state indicating factors have been divided in three parts like pressure, state and response.

2.3.1 Pressure

Pressure is a form of driving force that can directly or indirectly change the ecosystem quality (Singh et al., 2015). The pressure indicator also reflects the stress and impact from the natural environment or anthropogenic activity that can degrade the wetlands ecosystem (Jiang et al., 2005; Mai et al., 2005). The inappropriate development of human beings creates great stress on the river and riparian wetlands of flood plain regions (Talukdar and Pal, 2020a). Considering the eco-hydrological state of the study area, and based on previous studies seven pressure parameters such as APF, LST, LULC change, distance from the road, distance from built-up land, distance from agricultural land, population density, etc. were used to assess the effect of humans on the ecosystem (Sun et al., 2019; Wu et al., 2020; Das et al., 2020).

2.3.1.1 Agricultural presence frequency

Agriculture encroachment is a leading factor for wetland degradation in the alluvial environment (Saha and Pal, 2019; Talukdar and Pal, 2020b). The expansion of agriculture in the surrounding wetland may negatively affect the wetlands (Junk et al., 2013). The seasonal wetlands and agricultural land in the floodplain region are highly dynamic (Pal and Talukdar, 2018). The single dated image reflects the result of that year, so we used multi-dated images for agricultural presence frequency analysis. In this study, Landsat imageries of each year from 1980 to 2020 of the post-monsoon periods were taken to detect the agricultural land. Normalized difference vegetation index (NDVI) spectral indices have been applied to detect agricultural land. The NDVI values ranges 0.2 to 0.4 could reflect the cropland in the Barind

region. It has been decided based on 221 ground control points and validated by applying Kappa statistics (K). The calculated Kappa coefficient for the year 2018-2020 ranges from 0.81 to 0.85, indicating the good reliability of NDVI images and ground reality. Each NDVI map has been classified into a binary map (1= cropland and 0= non cropland). Finally, all the binary maps have been integrated following equation 2 to prepare the agricultural presence frequency map. The APF techniques were used (Eq. 2) to estimate the agricultural dominance status for both phases.

$$NDVI = \frac{b_{NIR} - b_{red}}{b_{NIR} + b_{red}} \dots\dots\dots (1)$$

Where NDVI is Normalized difference vegetation index, b_{NIR} is the near infrared band and b_{red} is the red band.

$$APF_{pj} = \frac{\sum_{i=1}^{N_x} IFP_{ij}}{N_x} \times 100 \dots\dots\dots (2)$$

Where, APF_{pj} represents the agriculture presence frequency of the pixel j in percentage of the total number of considered images (N_x). FAP_{ij} signifies frequency of agriculture presence at i^{th} pixel.

2.3.1.2 Land surface temperature

LST is an important physical parameter in the surface process, which plays a potential role as a global indicator of the status of wetlands and changes in their hydrological state, which is closely linked to LULC changes (Muro et al., 2018). It also regulates the physical, chemical, soil water, and vegetation condition of the wetlands (Du et al., 2019). LST of the individual year has been estimated according to the guidelines of the Landsat Project Science Office (2002) and using eq. (3) (Pal and Ziaul, 2017; Debanshi and Pal, 2020a) from Landsat images. The average LST map has been computed for both phases using yearly LST images.

$$LST = T_B / [1 + \{\lambda * T_B / \rho\} * \ln \varepsilon] \dots\dots\dots (3)$$

where, LST = Land Surface Temperature, T_B = At satellite temperature, λ = wavelength of emitted radiance in meters, $\rho = h * c / r$, h = Planck's constant, r = Boltzmann constant, and c = velocity of light ε = Land surface emissivity.

2.3.1.3 Distance from road

Urban growth, infrastructural development often plays a negative role in wetland transformation (Athukorala et al., 2021). There is evidence that environmental degradation is very much related to economic growth (Athukorala et al., 2021). Construction of roads across wetland tract is responsible for wetland conversion, wetland fragmentation, and ecological disturbances. Wetland fragmentation creates a susceptible environment for wetland ecological disturbances. The wetland in very proximity to road networks is very susceptible to conversion. Road networks have been traced from Google earth separately for pre-dam and post-dam phases. Distance map from roads has been prepared for both the cases in the ArcGis environment.

2.3.1.4 Distance from agriculture land

The extension of agricultural land in the flood plains region often creates conflict with the existing wetland (Pal and Saha, 2019; Pal and Talukdar, 2018). Fertile land in the alluvial plains facilitates agriculture and such agricultural extension often replaces wetland. Earlier it is mentioned that agricultural land has been demarcated based on the NDVI map computed from Landsat images. NDVI value 0.2 to 0.4 has been recognized as agriculture land. The proximity to agricultural land map has been derived using the Euclidean distance method considering the fact that an area located at very proximity to agricultural land is more susceptible to degradation or conversion than the area away from agricultural land.

2.3.1.5 Distance from built-up area

Built-up area induced wetland conversion is very evident in the case of urban proximate wetlands (Das and Basu, 2020). Wetland proximate built-up area not only creates a good chance for wetland reclamation but also qualitatively degrades the water quality and ecological ambient. Huge mixing of solid and liquid wastes are crucially responsible for wetland deterioration. Normalized Difference Built Index (NDBI) (Eq. 4) is used for deriving built up land from Landsat images. As the built-up feature is not so dynamic like seasonally inundated wetland and agriculture, the frequency approach has not been adopted in this case. Only recent year's images for both periods have been taken for developing built-up area maps. Proximity to built-up area maps have been done in the same way through which proximity to APF was prepared using Eq. 4. NDBI value ranges between -1.0 to 1.0. The threshold value of the built-up area is 0.14 and -0.038 for Landsat TM and Landsat OLI respectively instead of 0 as delimited by Pal and Ziaul (2017).

$$NDBI = \frac{b_{MIR} - b_{NIR}}{b_{MIR} + b_{NIR}} \dots \dots \dots (4)$$

2.3.1.6 Population density

Population density is a major determinant of creating pressure on the wetland (Ziaul and Pal, 2017; Nasirian et al., 2019) Population density (PD) defines the number of people lived per unit area. The village-wise population data has been collected from the Census report (Census of India, 1991 and 2011). The final population density map has been prepared using IDW (Inverse Distance Weighting) method.

2.3.1.7 Land use land cover change

The alluvial flood plain region is very dynamic due to anthropogenic pressure (Talukdar et al., 2020a; Singha et al., 2020). The changing character of LULC is very dynamic in this region due to huge population density and infrastructural development. The LULC change plays a vital role for wetlands degradation as well as eco-hydrological status. The LULC maps have been derived from satellite images using supervised image classification techniques (maximum likelihood classifier) in ERDAS software environment. The classification LULC map has been classified into five LULC classes like vegetation, waterbody, agricultural land, agricultural land with seasonal fallow and built-up area. Kappa coefficient has been calculated using equation 5. GCPs for the LULC map of post-dam condition and it is found that the classified LULC map has very good agreement with ground reality (K=0.81).

$$K = \frac{N \sum_{i=1}^r X_{ii} - \sum_{i=1}^r (X_{i+} * X_{+i})}{N^2 - \sum_{i=1}^r (X_{i+} * X_{+i})} \dots \dots \dots (5)$$

where N = total number of pixels; r = number of rows in the matrix; X_{ii} = number of observations in row i and column i ; x_{i+} and x_{+i} are the marginal totals for row i and column i , respectively.

2.3.2 State

The pressure system plays a dominant role in changes in wetlands, including wetland area, land use structure, habitat quality, etc. It can directly affect the ecosystem services, function of the wetland ecosystem (Zhang and Xu, 2017). Eco-hydrological state parameters refer to the components which can reflect the changes in the environmental factors, which are developed

under the long-term impact of abiotic and biotic elements. Thirteen state parameters (PD, PR, PRD, SHDI, MSIDI, SHEI, MSIEI, wetland depth, turbidity index, chlorophyll-a, Secchi disk depth, total phosphorus, range of variability have been taken into account in the study.

2.3.2.1 Patch Density

The overall degree of patch differentiation and fragmentation of wetland landscape is expressed by patch density (Wu et al., 2020). Greater patch density signifies higher degree of landscape fragmentation (Wu et al., 2020; Debanshi and Pal, 2020b). The patch density (PD) has been calculated following equation 6.

$$PD = \sum N_i / \sum A_i \dots\dots\dots (6)$$

Where, PD denotes patch density (PD), Ni is the number of patches in the landscape and Ai is the total area (m²) of the landscape.

2.3.2.2 Patch Richness

Patch richness is a key element of landscape structure because the variety of landscape elements present in a landscape can have an important influence on a variety of ecological processes. Patch richness (PR) measures the number of patch types in a particular landscape which was calculated from Landsat imageries using the equation. (7).

$$PR = m \dots\dots\dots (7)$$

where PR denotes Patch Richness and m is the number of patch types in the landscape.

2.3.2.3 Patch Richness Density

Patch richness density standardizes richness to a per area basis that facilitates comparison among landscape. PRD density indicates the average number of land-use types per 100 hectares (Tomaselli et al., 2012; Sun et al., 2016). PRD has been calculated following equation 9.

$$PRD = \sum N_i / \sum A_i \dots\dots\dots (9)$$

293 where *PRD* denotes Patch Richness Density, *N_t* is the number of patch types and *A_i* is the
 294 total area (m²) of the landscape.

295 2.3.2.4 Shannon's Diversity Index

296 SHDI is a popular measure of diversity in a community ecology landscape. Shannon's
 297 Diversity Index represents the species richness (number of different species) present in the
 298 particular landscape (Shannon and Weaver, 1949). SHDI has been calculated following
 299 equation 10.

$$300 \quad SHDI = - \sum_{i=1}^m P_i \cdot \ln P_i \quad \dots\dots\dots (10)$$

301 where SHDI Shannon's Diversity Index, *P_i* is the proportion of land occupied by *i* patch type

302 2.3.2.5 Modified Simpson's Diversity Index

303 MSIDI is a classic scalar ecological indicator which is used by various researchers in ecological
 304 status analysis in wetland ecological studies (Yang et al., 2020). SHDI has been calculated
 305 following equation 11.

$$306 \quad MSIDI = - \sum_{i=1}^m P_i^2 \quad \dots\dots\dots (11)$$

307 where MSIDI is the Modified Simpson's Diversity Index, *P_i* is the proportion of land occupied
 308 by *i* patch type.

309 2.3.2.6 Simpson's Evenness Index

310 SIEI is the species evenness (or relative species abundance) in a community is another factor
 311 that affects diversity of the landscape (Nayak et al., 2020). One of the most frequent methods
 312 of evenness measurement is Simpson's evenness index is calculated as the following equation
 313 12.

$$314 \quad SIEI = \frac{1 - \sum_{i=1}^m P_i^2}{1 - \left(\frac{1}{m}\right)} \quad \dots\dots\dots (12)$$

where P_i is the proportion of land occupied by i patch type and m is the number of patch types present in the landscape.

2.3.2.7 Modified Simpson's Evenness Index

The Modified Simpson's Evenness Index is calculated as follows:

$$MSIEI = \frac{-\ln - \sum_{i=1}^m P_i^2}{\ln m} \dots\dots\dots (13)$$

where P_i is the proportion of land occupied by i patch type and m is the number of patch types present in the landscape.

2.3.2.8 Wetland Depth

The water depth of wetland is ecologically significant for sustaining different wetland species like fish, birds, plants, etc.) who prefer to live at different ecological depth niches (Lantz et al., 2011; Asher et al., 2017). Therefore, wetlands having maximum depth provides higher habitat richness compared to a wetland having low depth (Chen et al., 2020). Due to the absence of spatiotemporal datasets, wetland depth mapping is very difficult and time-consuming over a wide geographical region. The recent work calibrated the NDWI map of both phases with wetland depth data at 33 field sites from different parts of the study region. The linear regression method is used to estimate the wetland depth. The computed regression slope used for depth calibration is 14.1051 from the NDWI image. Various researchers in worldwide like Khatun et al. (2021); Donchyts et al. (2016) have also implemented same approaches for water depth mapping from satellite images.

2.3.2.9 Turbidity Index

Turbidity is an optical determination of water clarity. Turbidity can be used as a surrogate for suspended solid and total phosphorous concentration in many aquatic systems like rivers, lakes, wetlands etc. (Jones et al., 2011). Soil erosion, urban waste water, suspended solid materials, algal growth are the major sources of turbidity in wetlands (Shen et al., 2019). Remote sensing helps to obtain an optical measure of water turbidity. Lacaux et al. (2007) developed an algorithm to estimate the water turbidity using remote sensing data specifically for ponds and inland waters, and the same equation (14) has been used here for computing turbidity levels.

$$NDTI = \frac{b_{red} - b_{green}}{b_{red} + b_{green}} \dots\dots\dots(14)$$

2.3.2.10 Chlorophyll-a

Chl-a is playing a dominant role to continue the photosynthetic process, which is known as a photosynthetic pigment found in the green floral community including algae (Wetzel et al., 2001). A biological eco-environment like wetlands requires an optimum concentration of phytoplankton and algae, which is also treated as the main producer of aquatic ecosystems (Yang et al., 2016). Landsat Operational Land imager (OLI) and Landsat Thematic Mapper (TM) data and consequent laboratory measurement have been used to estimate Chlorophyll-a (Chl-a) concentration. The most suitable band ratio has been identified by performing Pearson Correlation analysis between Chlorophyll-a concentration and possible band ratio from the study points. A model ranking method is used to set up the best regression model. The following are the best regression models for estimating Chl-a (15).

$$InChl_a = 1.432 - 1.195In(TM4) + 1.239Ln(TM2) \dots\dots\dots (15)$$

2.3.2.11 Secchi Disk Depth

The Secchi disk depth (SDD) is also known as ‘water clarity’ or ‘transparency’ in aquatic science, is an important parameter of water quality (Wernand, 2010). Therefore, the SDD has been a routine measurement in field surveys of aquatic environments using a Secchi disk since the 1860s (Secchi, 1864). In recent times Remote sensing data is widely used for retrieving the SDD because of its wide application and large aerial coverage (Carlson, 1977). Field specific data of 20 sites have been used to calibrate SDD from image data and the regression model used here for calibrating the image data is mentioned in equation 16.

$$InSDD = 2.925 - 0.629In(TM4) - 0.515Ln(TM2) \dots\dots\dots (16)$$

2.3.2.12 Total Phosphorus

Agricultural practice is one of the vital human activities that degrades the surrounding ecosystem. For instance, a huge amount of fertilizers, pesticides and herbicides from the agriculture sector are responsible for degrading the wetlands ecosystem as well as water quality and biotic integrity (Donner, 2003; Pal and Talukdar, 2018). The excessive use of fertilizers increases discharge of nutrients from agricultural sectors into the adjacent receiving streams,

wetlands etc. (Riseng et al., 2011). The higher amount of sediments and nutrients discharged from agricultural sectors to water bodies have resulted in widespread seasonal hypoxia in many areas around the globe (Dalu et al., 2019).

2.3.2.13 Range of Variability

There are various methods such as the twentieth and eightieth percentile, 1 standard deviation (SD), 2SD, etc. for estimated ecological flow (Richter et al., 1997). Such approaches are widely implemented for estimate river flow assessment but it is rarely implemented for wetland studies. The Range of variability approach (RVA) proposed by Richter et al. (1997) was applied to estimate ecological flow state. Mean± 1SD is used to compute the higher and lower threshold limits of water of each pixel of the wetlands applying water depth calibrated NDWI images of the various seasons. Mean±1SD is reflecting hydro-ecological status, if the value is less than Mean-1SD is treated as an eco-hydrologically stressed condition and if it is more than Mean+1SD is an eco-hydrologically affluent condition. Failure eco-hydrological rate is also calculated from above mentioned thresholds. After that, RVA thresholds of pre-dam phases of the selected periods have been computed and converted into binary characters for assigning 0 value to the Mean±1SD and >Mean+1SD (eco-hydrologically relevant and affluent) and 1 to the <Mean-1SD class (eco-hydrologically stress state). Season-specific yearly binary images are averages using the equation. 17. The range of failure rate ranges from 0- 100%, where the value near 0 means very least failure rate and near 100% represents the high rate of failure rate showing ecological distress situation.

$$FR_{EW} = \left(\frac{\text{Frequency of NDWI}_{FEW}}{\text{Total frequency of NDWI}_{Post}} \right) \times 100 \dots \dots \dots (17)$$

2.3.2.14 Hydroperiod

The water availability in a wetland throughout the year is known as hydro-period (Bertassello et al., 2019; Atta-Darkwa et al., 2020). Perennial wetlands provide better habitat than seasonal or ephemeral wetlands due to their long period of water availability and biological interaction (Park et al., 2019; Zhu et al., 2020). Long hydro-period of wetlands provides the optimum conditions for a wider spectrum of species than wetlands having a short hydro-period (Mukherjee and Pal, 2021). Monthly wetland maps derived from satellite images have been used to prepare a hydro-period map. Each wetland map has been converted into binary form assigning the value 1 for wetland and 0 for non wetland. The monthly binary map has been summed up in ArcGis environment for deriving a hydro-period map (Eq. 18).

$$H_p = \sum_{i=1}^n mthBNDWI \dots\dots\dots (18)$$

Where, H_p = Hydro-period, $mthBNDWI$ = Binary NDWI images of each month of a year.

H_p = summation of B_{NDWI}

B_{NDWI} = Binary NDWI images of each month of a year.

2.3.3 Response

The response indicators refer to the effect of pressure parameters as well as prevent, mitigate, or restore the unfavourable ecological changes (Jiang et al., 2005; Sun et al., 2019). In this study five response parameters (wetland fragmentation, ecosystem service value, eco-hydro deficit and eco-hydro surplus, change rate of water presence and wetland depth rate) has been selected for eco-hydrological state analysis.

2.3.3.1 Wetland Fragmentation

Wetland fragmentation due to natural or anthropogenic activities is a common issue of wetland degradation in third world countries (Pal and Talukdar, 2018). There are many ways to wetland fragmentation like agricultural expansion, construction of roads, buildings etc. (Atasoy, 2018; Ledda, 2019). Landscape Fragmentation Tool in ArcGis has been used for analyzing wetland fragmentation which was launched by the Centre for Land Use Education and Research (CLEAR) in 2002 (CLEAR, 2002). The fragmentation tool provides six hierarchical categories of fragmented indices such as patch, edge, perforated, small core, medium core and large core etc. The patch indices denote ecologically vulnerable and the large core denotes ecologically feasible land units (Vogt et al., 2007; Pal and Talukdar, 2018).

2.3.3.2 Ecosystem Service Value

Ecosystem services refer to the various benefits to human offers by the natural environment (Costanza et al., 2014). The ecosystems offer a range of tangible food, fresh water, fodder, various raw materials etc., and intangible services like carbon sequestration, climate regulating, water purification etc. The well-known approaches to estimated ESV of an ecosystem are the benefit transfer approach (BTA) (Costanza et al., 1997 and 2014), simulated market approach (Schmidt et al., 2016) etc. In this study, a simple BTA was used to estimate the ESV (Eq.19).

$$ESV = A_k \times VC_k \dots\dots\dots (19)$$

where ESV is denoted ecosystem service value, A_k is the area of each wetland class and VC_k is the value of coefficient these classes.

2.3.3.3 Measuring eco-hydrological deficit

Flow duration curve (FDC) is used for computing eco-surplus and deficit states. For this analysis median annual water depth duration curves for both undisturbed (pre-dam) and disturbed (post-dam) phases. When the direction of the controlled median FCD remains below unregulated median flow, the status is denoted as eco-hydro-deficit and the opposite condition denoted as eco-hydro surplus (Vogel and Fennessey, 1995; Talukdar and Pal, 2019). This approach clearly reflects the gain or loss of water depth in the implementation of artificial control like dam construction (Vogel et al., 2007). This approach is frequently used in the case of river flow study but very rare in wetland studies.

2.3.3.4 Change rate of water presence frequency

WPF refers to the frequency at which water appears in a pixel over time (Borro et al., 2014; Debanshi and Pal, 2020a). In the study area WPF is computed at annual scale in post monsoon for both pre and post dam conditions. For mapping the WPF map, NDWI of each year has been prepared from Landsat images for all the years (from 1987 to 2020) and each map is transformed into a binary map denoting 0 to non-wetland pixels and 1 to wetland pixels. Time series binary maps have been added and expressed as percentage (Eq. 20). WPF value is 100% if water appears in a pixel all through the selected time period. The change rate of water presence frequency has been derived from WPF map of previous and most recent times for both pre and post dam phases.

$$WPF_p = \frac{\sum_{i=1}^n X_j}{N} \dots\dots\dots (20)$$

where WPF_p is calculated water presence frequency for p pixel. X_j is the frequency of j th pixel in image X having water appearance, and N is the number of years taken.

2.3.3.5 Change rate of wetland depth

Earlier it is mentioned how the depth map is developed from the Landsat image. Change detection is carried out for computing change matrix of water depth.

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467 **Figure. 2** Shows the data layers for Pressure of wetland eco-hydrological state (EHS) for pre-dam (post-monsoon) and post-dam (post monsoon)
468 phase: (a) Agricultural Presence Frequency (b) Land Surface Temperature (LST) (c) Distance from the road (d) distance from the agricultural
469 land (e) Distance from built-up area (f) population density (g) Land use and land cover (LULC) change.

Figure 3

Figure 4

Figure 3 and 4 Shows the data layers for State of wetland eco-hydrological state (EHS) for pre-dam (post monsoon period) and post-dam (post monsoon) phase: (a) Patch Density (b) Patch Richness (c) Patch Richness Density (d) Shannon's Diversity Index (e) Modified Shannon's Diversity Index (f) Simpson's Evenness Index (g) Modified Simpson's Evenness Index (h) Wetland Depth (i) Turbidity Index (j) Chlorophyll-a (k) Secchi Disk Depth (l) Total Phosphorus (m) Range of Variability approach (n) Hydroperiod

Figure 5 Shows the data layers for Response of wetland eco-hydrological state (EHS) for pre-dam (post monsoon period) and post-dam (post monsoon) phase: (a) Wetland Fragmentation (b) Ecosystem Service Value (c) Eco-Deficit (d) Change rate of water presence frequency (e) Change rate of wetland depth

2.4 Machine learning algorithms

2.4.1 Artificial neural network

The interconnected neurons that operate the data and interact with other components are the main characteristics of ANN (Svozil et al., 1997). The independent statistical distribution of the data sets, self-learning, and associative memory are the main characteristics of the ANN model. ANN can handle some unknown information hidden in the data sets. ANN model provides linear or non-linear models and single multi-layer networks (Dou et al., 2015). The ANN model has frequently been used in classification, regression, recognition, autocorrelation, prediction, and many other fields. ANN is a very popular ML algorithm and has been widely used to identify and solve various environmental problems such as landslides, floods, wetland prediction, gully erosion, etc. (Garosi et al., 2018; Dtissibe et al., 2020; Debanshi et al., 2020a; Saha et al., 2020).

2.4.2 REPTree

The Reduced Error Pruning Tree (REPTree) is known as a rapid decision tree learner based on C4.5. It's a conceptual approach for attempting to solve the decision learner problems (Alabdulwahab and Moon, 2020). The REPTree algorithm creates a decision tree based on knowledge gain or variance reduction (Quinlan, 1987). It deals with missing values by splitting the data sets using fractional instances using C4.5 and creates multiple trees in various interactions and selects the best form of all trees created. REPTree was introduced as a way to reduce tree structure complexity while maintaining classification accuracy and also solved the data overfitting problems. It forms a decision tree by splitting and pruning the regression tree based on the highest information gain ratio value (Alabdulwahab and Moon, 2020). The REPTree model was successfully applied in different fields such as modelling gully erosion, modelling flood susceptibility, deforestation probability etc. (Chen et al., 2019; Nhu et al., 2020; Saha et al., 2020).

2.4.3 M5P

Quinlan (Quinlan et al., 1992) first discovered the M5P algorithm which is the modification version of M5 algorithm. The extension version of M5P model applied in this recent study. This model is capable of efficiently handling large numbers of data sets with a high number of attributes and dimensions (Solomatine et al., 2003). This model smoothly handles missing data sets. In the beginning, T is associated with a leaf storing linear regression function or split into subsets accounting for the outputs, and then the same process is recursive for the subsets. In this process, selecting proper attributes to split T, in order to minimize the expected error at a particular node, requires a splitting criterion, and standard deviation reduction is the expected error reduction, calculated by the following equation (21).

$$SDR = sd(T) - \sum_i \frac{|T_i|}{|T|} sd(T_i) \quad \dots\dots\dots (21)$$

where T is a group of samples that archives the node; T_i is the result of splitting the node in terms of the chosen attribute. The model finally chooses the split that maximizes the expected error reduction.

2.4.4 Support vector machine

SVM is well-known as a supervised non-parametric statistical ML technique. The concept of SVM is based on decision planes, which is defined as the plane of separation of different objectives or different class membership (Choubin et al., 2019). It can work with different types

of variables like continuous, categorical as well as linear and non-linear data sets in different class members. The basis of this technique is separating hyper-plane creation in the training dataset. The mathematical function used to transform data is known as the kernel function (Tehrany et al., 2015). In the SVM model, to separate the original input space, an optimal hyper-plane is used for this purpose. The kernel function is used for data transformation, which is divided the entire dataset into flood and non-flood categories and it is determined by 1 and 0 respectively. Identification of proper kernel function shows the ability of SVM model. The kernel functions of SVM models were classified into four classes, such radial basis kernel (RBF), sigmoid kernel (SG), linear kernel (LN) and polynomial kernel (PL). Commonly in remote sensing environments PL and RBF kernel has been used (Maxwell et al., 2018).

RBF kernel is commonly used in SVM techniques for the higher performance and higher level of accuracy of the model than the other traditional methods. (Knorn et al., 2009; Zhang et al., 2019). According to previous literature (Hong et al., 2018; Bui et al., 2012), RBF kernel was used for better performance compared to other kernels in flood susceptibility issues. Therefore, RBF kernel function was applied to identify the flood probability zones in the recent work. This method was extensively applied in flood susceptibility context (Zhao et al., 2019; Sachdeva et al., 2017; Sahana et al., 2020). The major drawbacks to modelling of SVM modelling are generally associated with its difficulty in capturing important parameters (Choubin et al., 2019).

2.4.5 Random subspace

In 1998, Ho first developed RS classifier, which is defined as classic integrated ensemble algorithm (Ho, 1998). The RS model was widely used in environmental science for solving environmental problems (Lee et al., 2017; Chen et al., 2019; Wang et al., 2019). RS is a well-known ensemble ML algorithm that offers a pseudo-randomly chosen subsets to each and every classifier and outputs are combined by voting. RS classifiers improve the weak classifier efficiency (Wang and Tang, 2006) and improve the accuracy of classification of individual classifiers (Pham et al., 2017). The training data also modified by RS classifier; however, this modification is carried out in the features space. Handling large data sets and solving the over fitting problems become more popular in RS model (Onan, 2016). This method may be beneficial from using random subspace for both constructive and aggregation the classifier. Small sample sized issues can easily be handled by RS algorithms (Yaman et al., 2018).

2.4.6 Bagging

The Bagging algorithm is a very popular ML algorithm, which was widely used to develop ensemble ML models by coalescing with different algorithms (Prasad et al., 2006; Chapi et al., 2017). Breiman (1996) first introduced the bagging technique, which is a “bootstrap” (Efron and Tibshirani, 1995) ensemble technique that generate multiple types of classifiers and also generated an aggregated classifier (Pham et al., 2018; Piao et al., 2015). The statistical bootstrapping techniques employ random sampling with replacement to obtain various samples from the training dataset and a decision tree has been constructed based on the each of obtained subset for training dataset (Chen et al., 2018). The training dataset is continuously replaced by drawing random samples (Piao et al., 2015). By combining all the generate models, the final model is performed (Chen et al., 2018). Numerous studies stated that the bagging predicted environmental problems in very high accuracy (Chen et al., 2019; Dou et al., 2019; Wu et al., 2019; Hosseinalizadeh et al., 2020; Shahabi et al., 2020;). The bagging algorithm enhanced the model performance to predict any environmental issue by leasing the variance of the prediction errors (Prasad et al., 2006). Previous literature shows that bagging shows the higher accuracy for predicting flood (Chen et al., 2020; Arabameri et al., 2020), landslides (Truong et al., 2018), gully erosion (Dou et al., 2019) modelling.

3. Validation and accuracy assessment

3.1 Statistical tests

Receiver Operating Characteristics (ROC), Field based validation, Friedman test have been used to validate and compare the model performance. ROC curve is a widely accepted method to determine the model efficiency. In this study, ROC curves have been computed using 200 field sites data where Area under curve (AUC) values could show the ground reality of the ML models (Nohani et al., 2019). AUC is the function of model sensitivity and specificity, which are calculated with the help of four possible sets of ground truth reality, true positive, true negative, false positive and false negative (Singha et al., 2020). Equation 22-24 shows the mathematical formulations of sensitivity, specificity and accuracy.

$$\text{Sensitivity} = \text{true positive} / (\text{true positive} + \text{false negative}) \quad (22)$$

$$\text{Specificity} = \text{true negative} / (\text{true negative} + \text{false positive}) \quad (23)$$

$$\text{Accuracy} = (\text{true positive} + \text{true negative}) / (\text{true positive} + \text{true negative} + \text{false positive} + \text{false negative}) \quad (24)$$

The value of AUC of ROC curve ranges from 0 to 1, where 1 indicates the excellent performance of classification, while 0.5 indicates non-accurate performance of the model (Singha et al., 2020; Talukdar et al., 2021). The AUC value has been computed using the SPSS software environment. Friedman tests (Friedman, 1937) have been applied to identify the significant variances among the ML models (Beasley and Zumbo, 2003).

3.2 Field based Ecosystem Service Potentiality analysis

The potential supply of Ecosystem service (ES) can be defined as the “hypothetical maximum performance of a given land cover to supply a specific ecosystem service” (Burkhard et al., 2012, 2014). Ecosystem service potentiality (ESP) approach has been used in this study to estimate the ecosystem service potential in different eco-hydrological state zones (Montoya-Tangarife et al., 2017). Ecosystem service potentiality approach has been used in this study to estimate the ecosystem service potentiality of different eco-hydrological state zones. Ecosystem service matrix has been developed to calculate the ESP status of different eco-hydrological state zones. The expert-based assessment techniques were applied to calculate the ecosystem service potentiality matrix. Total thirty-one services covering regulating service (11), provisional service (14) and cultural service (06) have been selected from previous literatures and ground reality (Fisher et al., 2019; Burkhard et al., 2012; Barral et al., 2012; Burkhard et al., 2014; Montoya-Tangarife et al., 2017; Mukul et al., 2017) as mentioned in Table 4.

3.2.1 Expert based assessment

The expert-based assessment approach has been applied in this study to calculate the ecosystem service potentiality matrix. Expert are approached and asked to provide the potential score of each ecosystem services using a rating scale ranges from 0 (no potential) and 5 (maximum potential) based on the Likert scale (Vihervaara et al., 2010; Koschke et al., 2012; Burkhard et al., 2012). A short description of ecosystem services provided to the expert. Each expert has been providing detailed instructions on how to fill out the potential matrix table with potential scores. An average score has been calculated based on expert opinion in different ES groups and finally ESP has been derived from average expert-based opinion scores (table 4).

Table 4 Selected Ecosystem services taken for expert-based assessment

Ecosystem service groups	Ecosystem service	References
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Regulating service	Global climate change	Burkhard et al., 2013; Montoya-Tangarife et al., 2017
	Local climate regulation	Vihervaara et al., 2010; Burkhard et al., 2013
	Air quality regulation	Burkhard et al., 2014; Lin et al., 2019
	Water flow regulation	Burkhard et al., 2014; Montoya-Tangarife et al., 2017
	Water purification	Burkhard et al., 2014; Montoya-Tangarife et al., 2017
	Waste treatment	Burkhard et al., 2014; Lin et al., 2019
	Nutrient regulation	Burkhard et al., 2012; Quyen et al., 2017
	Natural hazards regulation	Quyen et al., 2017; Burkhard et al., 2014
	Pollination	Bartholomée et al., 2019; Lin et al., 2019
	Paste and diseases control	Quyen et al., 2017; Koschke et al., 2012
	Erosion Prevention	Olson et al., 2017; Koschke et al., 2012
Provisioning service	Food	Pritchard et al., 2019; Koschke et al., 2012
	Biomass for energy	Koschke et al., 2012; Vihervaara et al., 2010
	Fodder	Burkhard et al., 2014; Lin et al., 2019
	Livestock (Domestic)	Burkhard et al., 2013; Montoya-Tangarife et al., 2017
	Fiber	Pritchard et al., 2019; Olson et al., 2017
	Timber	Burkhard et al., 2014; Montoya-Tangarife et al., 2017
	Wood fuel	Pritchard et al., 2019; Lai et al., 2018
	Fish & Edible algae	Wondie, 2018; Lai et al., 2018
	Medicinal resources	Pritchard et al., 2019; Burkhard et al., 2012
	Freshwater supply	Burkhard et al., 2012; Burkhard et al., 2014
	Minerals resources	Burkhard et al., 2014; Lin et al., 2019
	Transportation (Boat, ferries etc.)	Bartholomée et al., 2019; Lin et al., 2019
	Abiotic energy sources	Quyen et al., 2017; Koschke et al., 2012
Cultural services	Recreation & tourism	Wondie, 2018; Lin et al., 2019
	Landscape aesthetics & inspirations	Quyen et al., 2017; Koschke et al., 2012
	Knowledge system	Koscheke et al., 2012; Kopperoinen et al., 2014
	Religious and spiritual experiences	Quyen et al., 2017; Koscheke et al., 2012

	Cultural heritage & cultural diversity	Burkhard et al., 2013; Montoya-Tangarife et al., 2017
	Natural heritage & natural diversity	Koscheke et al., 2012; Kopperoinen et al., 2014

Figure. 6 Flow chart of the entire work

4. Result

4.1 Wetland area between pre and post dam condition

The wetland map was derived using NDWI (Normalized difference water index) of each year in pre-dam and post-dam phases and the areal extent of NDWI maps shows a declining trend of wetland over the advances of time. Wetland maps of the post-monsoon season of 1988 (pre-dam period) was 55.22 km² which has been reduced to 15.62 km² in 2020 (post-dam period). The lower reach of the mainstream is dominated by well-defined seasonal riparian wetland.

Wetland extent is found high during monsoon and post-monsoon seasons triggered by high monsoonal rainfall.

4.2 Eco-hydrological state modelling

The wetland eco-hydrological state (EHS) zone has been developed using six machine learning (ML) models (Figure 7). Each EHS map has been classified into very poor, poor, moderate, good and very good categories applying natural break methods. The very good and good EHS zones are found in the lower and middle part (pre-dam) and lower part (post-dam) of this basin due to the presence of major river and river-side wetlands. The both sides of the main river have been facing very good and good EHS zones due to lateral spread of river water.

Table 5 represents the calculated area of each EHSZ zone of all the ML algorithms. Out of total area, 35.46%, 37.35%, 40.23%, 39.51%, 32.94%, 57.90% area in pre-dam and 9.34%, 9.40%, 9.33%, 9.24%, 9.79%, 9.79% area in post-dam period fall into very good EHS zone under ANN, REPTree, M5P, RS, SVM, Bagging models respectively indicating sharp declining of area under this category. The ANN, REPTree, M5P, RS, SVM and Bagging models have predicted 15.04%, 21.53%, 22.96%, 22.82%, 23.08% and 24.72% areas under very poor EHS zone in pre-dam condition (Table 5). In post-dam phase this areal extent has increased to 39.36%, 39.22%, 35.26%, 33.38%, 40.10% and 24.72% as predicted by ANN, REPTree, M5P, RS, SVM and Bagging model respectively under the same zone. Reduction of area under very good and increasing area under very poor EHS zones clearly signifies the degradation of wetland. The very good EHS zones are mainly found in the main channel. It is demarcated that the quality of ESH has continuously decreased away from main stream. In some areas, poor quality of EHS is also identified at every vicinity to the main channel. Most of the cases very poor and poor EHS zones are found at the fringe area of the riparian corridor. Rate of wetland deterioration is very fast in the middle part of the mainstream in compared to lower reach.

Figure 7 showing wetland eco-hydrological state mapping using advance ML algorithms.

657 **Table. 5** Area under different Eco-hydrological state zones using advanced ML algorithms for both phases.

	Class	ANN		REPTree		M5P		RS		SVM		Bagging	
		Area (km ²)	Area in %	Area (km ²)	Area in %	Area (km ²)	Area in %	Area (km ²)	Area in %	Area (km ²)	Area in %	Area (km ²)	Area in %
Pre-Dam	Very Poor	20.33	15.04	31.55	21.53	33.629	22.96	33.43	22.82	33.82	23.08	36.21	24.72
	Poor	22.03	16.30	26.59	18.15	25.389	17.34	26.26	17.93	27.30	18.63	15.09	10.30
	Moderate	31.87	23.58	24.89	16.99	21.605	14.75	21.96	14.99	25.12	17.14	16.29	11.12
	Good	25.48	18.85	26.13	17.83	25.589	17.47	25.31	17.28	27.35	18.67	21.01	14.34
	Very Good	35.46	26.23	37.35	25.50	40.234	27.47	39.51	26.98	32.94	22.48	57.90	39.52
Post-Dam	Very Poor	23.67	39.36	23.59	39.22	19.84	35.26	19.27	33.38	24.12	40.10	23.89	39.72
	Poor	11.49	19.10	11.47	19.07	11.43	20.31	11.42	19.78	11.93	19.83	11.99	19.93
	Moderate	8.63	14.35	8.44	14.03	8.65	15.37	8.85	15.34	7.98	13.27	7.75	12.89
	Good	7.02	11.67	7.26	12.06	7.03	12.49	6.94	12.02	6.33	10.53	6.72	11.18
	Very Good	9.34	15.52	9.40	15.63	9.33	16.57	9.24	16.02	9.79	16.27	9.79	16.28

4.3 Validation and comparison of ML models

4.3.1 Statistical tests

The AUC of RoC for all individual ML models ranges from 0.852 to 0.950 and 0.905 to 0.929 for pre-dam and post-dam periods respectively showing the excellent agreement between the ML model and ground reality. Considering the AUC value REPTree (AUC=0.950) model is found as the best suited model followed by M5P (0.944), RS (0.944), Bagging (0.939), SVM (0.921) and ANN (0.852) respectively for pre-dam period. But in case of post-dam period, Bagging (0.929) model is found as the best representative model followed by SVM (0.921), RS (0.911), REPTree (0.911), ANN (0.906), M5P (0.905) respectively. Therefore, the REPTree (0.950) and Bagging (0.939) model could be treated as the best ML model for Eco-hydrological state modelling in the present study area (Figure 8). Friedman test explains the fact that whether there is any statistical difference among the results of the applied model. Result has clearly exhibited the fact that statistical difference among the models is significant at 100% level of significance (Table 6).

Figure. 8 Validation of ML models using ROC curve.

688 **Table. 6** AUC of ROC under different predicted ML algorithms of wetland eco-hydrological state (EHS) for pre-dam and post-dam period.

Pre-Dam period						Post-Dam period					
Area Under the Curve						Area Under the Curve					
Test Result Variable(s)	Area	Std. Error ^a	Asymptotic Sig. ^b	Asymptotic 95% Confidence Interval		Test Result Variable(s)	Area	Std. Error ^a	Asymptotic Sig. ^b	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound					Lower Bound	Upper Bound
ANN	0.85	0.026	0.000	0.802	0.903	ANN	0.91	0.02	0.000	0.867	0.945
REPtrree	0.95	0.013	0.000	0.924	0.975	REPtrree	0.91	0.018	0.000	0.875	0.946
M5P	0.94	0.014	0.000	0.916	0.972	M5P	0.91	0.02	0.000	0.865	0.945
RS	0.94	0.014	0.000	0.916	0.972	RS	0.91	0.018	0.000	0.876	0.947
SVM	0.92	0.02	0.000	0.883	0.96	SVM	0.92	0.019	0.000	0.884	0.959
Bagging	0.94	0.015	0.000	0.909	0.968	Bagging	0.93	0.017	0.000	0.896	0.962

689

690 **Table.7** Result of Friedman test

Pre-dam period				Post-dam period			
Model	Mean rank	Chi square	Significance level	Model	Mean rank	Chi square	Significance level
ANN	2.96	154.19	0.000	ANN	4.37	89.95	0.000
REPtrree	4.20			REPtrree	3.60		
M5P	3.41			M5P	3.37		
RS	3.20			RS	3.14		
SVM	4.56			SVM	3.56		
Bagging	2.68			Bagging	2.96		

691

692 **4.3.2 ESP based validation of eco-hydrological state models**

693 ESP is also used for validating the EHS models. Table 8 depicts the average rating of ESP under regulating, provisional and cultural services in
694 particular and total ESP in general for all the individual EHS zones. Result of ESP shows concurrences between EHS and ESP states. For

688 instance, total ESP is rated 3.8 in case of very good EHS zone followed by 3.4, 2.9, and 1.1 in good, moderate and very poor EHS zones
689 signifying the fact the wetlands areas characterized by poor EHS in having low ESP and vice-versa in case of qualitatively upgrades EHS zones.
690 This trend is also true when comparison is done between individual ESP categories with EHS zones (Figure 9).

691 **Table. 8** Ecosystem services potential (ESP) matrix of different Eco-hydrological states zones.

Wetland Ecosystem potential status	Regulating services	Global climate change	Local climate regulation	Air quality regulation	Water flow regulation	Water purification	Waste treatment	Nutrient regulation	Natural hazards regulation	Pollution	Past and present roles	Erosion Prevention	Provisioning services	Food	Biomass for energy	Fodder	Livestock (Domestic)	Fiber	Timber	Wood fuel	Fish & Wildlife	Aquaculture	Medicinal resources	Freshwater supply	Mineral resources	Transportation (Boat, ferries etc.)	Ambient energy sources	Cultural services	Recreation & tourism	Landscape aesthetics & inspiration	Knowledge systems	Religious and spiritual experiences	Cultural heritage & cultural diversity	Natural heritage & natural diversity	Total potential provision of ecosystem services
Very Poor	1.6	1.5	3.0	2.9	2.1	1.5	1.2	1.3	1.2	0.8	0.9	1.1	0.9	1.3	0.9	1.2	1.5	1.3	0.1	0.2	1.5	1.3	0.7	0.8	0.1	0.5	0.8	0.7	0.3	1.2	0.6	0.5	0.8	0.6	1.1
Poor	2.3	2.5	3.5	3.2	2.6	2.5	2.1	2.1	2.0	1.5	1.8	2.2	1.7	2.5	1.3	2.3	2.1	0.3	0.3	3.1	2.3	1.7	2.5	0.2	1.3	1.4	1.6	1.3	2.1	1.2	1.7	1.5	1.8	1.9	
Moderate	3.2	3.0	4.2	3.5	3.5	3.3	3.0	3.5	3.0	2.1	3.0	3.5	2.7	4.1	2.5	3.5	3.8	3.9	0.5	0.5	4.3	3.5	2.5	4.5	0.3	2.1	2.0	2.9	2.5	3.3	2.5	2.5	3.0	3.5	2.9
Good	3.8	3.5	4.6	4.0	4.5	4.0	3.5	4.2	3.5	2.5	3.3	4.0	3.1	4.5	3.5	3.9	4.2	4.4	0.8	0.6	4.7	4.2	3.0	4.6	0.5	2.3	2.2	3.4	3.0	3.5	3.2	3.0	3.5	4.0	3.4
Very Good	4.2	3.8	4.9	4.5	4.6	4.3	4.0	4.5	4.5	3.0	3.5	4.1	3.4	4.8	4.0	4.2	4.5	4.5	0.7	0.9	4.9	4.7	3.7	4.9	0.5	2.5	2.6	3.7	3.2	4.2	3.5	3.3	3.8	4.3	3.8

Figure. 9 Ecosystem services potentiality status of the wetlands in pre-dam and post-dam periods. It is developed calibrating the Eco-hydrological states models through field-based ecosystem services ranking.

5. Discussion

In this study, we have attempted to identify and monitor the changes in hydrological and eco-hydrological environments in the lower part of the Tangon river basin due to dam construction. Previous studies mostly demarcated the temporal changes of wetland area but hardly addressed the issue of eco-hydrological changes within the areal coverage of wetland which has broad implication from the perspective of comprehending ecological health and vitality of the wetland ecosystem and its proneness to be altered (Baker et al., 2007; Pal and Sarda, 2020). This work has considered a total 26 numbers of pressure-state-response parameters for delineating the eco-hydrological state of the wetland. Among the considered parameters, eco-hydro deficit, range of variability based wetland class, hydro-period, wetland depth, turbidity index parameters have been incorporated rarely for studying related studies but all these are very crucial for detecting ecosystem health or eco-hydrological state of the wetland (Talukdar and Pal., 2019; Pal and Sarda, 2020; Saha and Pal, 2019). The floodplain wetlands in deltaic region provide various ecosystem services for human well-being such as freshwater, food, raw materials, flood control, nutrient cycling and many intangible benefits like ecotourism, recreation and landscape aesthetics (Gren et al., 1995; MA, 2005; Uhel et al., 2010; Zorrila et

al., 2014). Wetland eco-hydrological states are considered ecologically diverse and the nature of the ecosystem is also very dynamic. So, the assessment of wetland EHS of wetlands is a very difficult task, due to the impact of controlling factors that vary spatially and temporally. Remote sensing time series data has been used to analyze EHS mapping because of wide data characteristics. Following the PSR framework, synthetic indices for pressure, state and response indicators, were developed which facilitate a rapid and quantitative assessment of eco-hydrological state.

In this study, wetland eco-hydrological state modelling has been carried out following PSR (Pressure-State-Response) framework including twenty-five conditioning parameters for both pre-dam and post-dam periods. The eco-hydrological state conditioning parameters (PSR framework) has been modelled using six widely used machine learning algorithms. The study reveals that the status of EHS status of the wetland in Tangon river basin has been degraded from pre-dam (1989) to post-dam (2020) periods. The result showed that pressure factors like agricultural expansion, intensification, lowering of water availability are very crucial determinants for growing degradation of wetland eco-hydrological state. After installation of dam across the river in 1989, 63% water flow is reduced, frequency of high flow pulses is decreased substantially, and frequency of low flow pulses is increased remarkably (Pal et al., 2019). Reduction of high flow level is again responsible for reducing flooding frequency and lateral spread of flood water in the riparian corridor. It also causes lowering water availability in the river flood fed wetlands. Damming effect has reduced flood prone area by 39% in Punarbhaba river, a river of Barind tract (Talukdar and Pal, 2019). It causes decline of hydro-period, water depth, water presence frequency etc. in post-dam period. These are very evident reasons behind degradation of eco-hydrological state of the wetland as found in the present study unit. Loss of connectivity between river and wetland not only hinders the water supply to the wetland but it also hampers the nutrient supply to the wetland, supply of fishes to the wetland and enhances the likelihood of pollution in the isolated wetland (Galib et al., 2018; Khatun et al., 2021). All these are against of good eco-hydrological state of the wetland. In damming after situation, degradation of EHS is also partially explained by these factors. Degradation of EHS has direct impacts on ecosystem productivity and services of the wetland. Based on the author's knowledge ML algorithms using field-based parameters have not been yet applied in previous works for modelling EHS in the world. Multi-model ensemble approach has been applied for predicting EHS in order to obtain a better scope for selecting the model with greater precision. ML models provide scope for objective solution of complicated

relations among the multiple parameters (Han et al., 2020). For validating the models apart from statistical approaches, the Ecosystem Service Potential (ESP) approach has been adopted considering 31 numbers of ecosystem service parameters. This approach of validating the EHS model is very novel. As the dataset for developing ESP have been collected from field experts, application of this for validating EHS models could be treated as justified. This method has some demerits since it is based on Likert scale and therefore absolute state is not clearly explained. Moreover, objectivity of the result is another issue that could be raised. However, this method is accepted by the scientific community as it accurately provides relative judgement in different places. This work is a good blend of ML modelling in PSR framework. Perhaps, this application is very rare and effective for delineating the EHS of wetlands hydrologically modified due to damming. Model validation part has emphasized both conventional statistical means and field-based ESP showing an unique approach to model validation. This study gives a good scope of further research like research toward developing more objective and quantitative results of ESP that could be used more objectively for validating the EHS model.

Conclusion

The present study has clearly identified that the in post-dam condition area under good and very good EHS zone has substantially reduced increasing the area under very poor EHS zone. Among the applied model, REPTree and Bagging models have been identified as the best representative ML model for delineating EHS. Expert based result of ESP also shows a very good concomitant with EHS result establishing the fact that ESP could be an effective means of model validation. The study strongly suggests if degradation of EHS of wetland is to be slackened down, immediately some steps like release of eco-flow in river, stop reclamation of wetland, emphasis on wetland use keeping it as wetland are very urgent. Considering the success of the ML models applied in different fields by the predecessors and very inspiring result of the present study, the present study further recommends to use ML models for multi-criteria decision making. While such modelling the validation part should be very strong and this study suggests to apply a field-based approach for model validation.

Acknowledgement

The second author of the article would like to thank the University Grants Commission (UGC Ref. No.3267/(SC)(NET-JAN.2017), New Delhi, India for providing financial support as a junior research fellowship to conduct the research work presented in this paper.

Data availability

The data that support the findings of this study are available from the corresponding author, [swadespal2017@gmail.com], upon reasonable request.

References

Alabdulwahab, S., & Moon, B. (2020). Feature selection methods simultaneously improve the detection accuracy and model building time of machine learning classifiers. *Symmetry*, 12(9), 1424.

Altıntaş, H., & Kassouri, Y. (2020). Is the environmental Kuznets Curve in Europe related to the per-capita ecological footprint or CO2 emissions?. *Ecological Indicators*, 113, 106187.

Arabameri, A., Pradhan, B., & Rezaei, K. (2019). Gully erosion zonation mapping using integrated geographically weighted regression with certainty factor and random forest models in GIS. *Journal of environmental management*, 232, 928-942.

Arabameri, A., Saha, S., Chen, W., Roy, J., Pradhan, B., & Bui, D. T. (2020). Flash flood susceptibility modelling using functional tree and hybrid ensemble techniques. *Journal of Hydrology*, 125007

Assessment, M. E. (2001). *Millennium ecosystem assessment*. Millennium Ecosystem Assessment.

Assessment, M. E. (2005). *Ecosystems and human well-being: wetlands and water*. World resources institute.

Atasoy, M., Anderson, C. J., & Atasoy, F. G. (2018). Evaluating the distribution of invasive woody vegetation around riparian corridors in relation to land use. *Urban Ecosystems*, 21(3), 459-466.

Athukorala, D., Estoque, R. C., Murayama, Y., & Matsushita, B. (2021). Impacts of Urbanization on the Muthurajawela Marsh and Negombo Lagoon, Sri Lanka: Implications for Landscape Planning towards a Sustainable Urban Wetland Ecosystem. *Remote Sensing*, 13(2), 316.

805 Atta-Darkwa, T., Asomaning, S. K., Agbeshie, A. A., Danso, E. O., Akolgo, G. A., Amankwah,
806 E., & Owusu, P. A. (2020). Assessment of physicochemical properties of Besease wetland
807 soils, Ghana. *African Journal of Agricultural Research*, 15(4), 509-523.

808 Baker, C., Lawrence, R. L., Montagne, C., & Patten, D. (2007). Change detection of wetland
809 ecosystems using Landsat imagery and change vector analysis. *Wetlands*, 27(3), 610-619.

810 Barral, M. P., & Oscar, M. N. (2012). Land-use planning based on ecosystem service
811 assessment: A case study in the Southeast Pampas of Argentina. *Agriculture, Ecosystems &*
812 *Environment*, 154, 34-43.

813 Bartholomée, O., & Lavorel, S. (2019). Disentangling the diversity of definitions for the
814 pollination ecosystem service and associated estimation methods. *Ecological indicators*, 107,
815 105576.

816 Basu, T., Das, A., & Pal, S. (2020). Application of geographically weighted principal
817 component analysis and fuzzy approach for unsupervised landslide susceptibility mapping on
818 Gish River Basin, India. *Geocarto International*, 1-24.

819 Beasley, T. M., & Zumbo, B. D. (2003). Comparison of aligned Friedman rank and parametric
820 methods for testing interactions in split-plot designs. *Computational statistics & data*
821 *analysis*, 42(4), 569-593.

822 Bertassello, L. E., Jawitz, J. W., Aubeneau, A. F., Botter, G., & Rao, P. S. C. (2019). Stochastic
823 dynamics of wetlandscapes: Ecohydrological implications of shifts in hydro-climatic forcing
824 and landscape configuration. *Science of The Total Environment*, 694, 133765.

825 Borro, M., Morandeira, N., Salvia, M., Minotti, P., Perna, P., & Kandus, P. (2014). Mapping
826 shallow lakes in a large South American floodplain: a frequency approach on multitemporal
827 Landsat TM/ETM data. *Journal of Hydrology*, 512, 39-52.

828 Breiman, L. (1996). Bagging predictors. *Machine learning*, 24(2), 123-140.

829 Burkhard, B., Kandziora, M., Hou, Y., & Müller, F. (2014). Ecosystem service potentials,
830 flows and demands-concepts for spatial localisation, indication and quantification. *Landscape*
831 *online*, 34, 1-32.

832 Burkhard, B., Kroll, F., Nedkov, S., & Müller, F. (2012). Mapping ecosystem service supply,
833 demand and budgets. *Ecological indicators*, 21, 17-29.

834 Carlson, R. E. (1977). A trophic state index for lakes 1. *Limnology and oceanography*, 22(2),
835 361-369.

836 Census of India, 1991&2011. Provisional Population Totals-India Data Sheet. Indian Census
837 Chakraborty, R., Talukdar, S., Basu, T., & Pal, S. (2018). Habitat identity crisis caused by the
838 riparian wetland squeeze in Tangon River Basin, Barind Region, India. *Spatial Information*
839 *Research*, 26(5), 507-516.

840 Chapi, K., Singh, V. P., Shirzadi, A., Shahabi, H., Bui, D. T., Pham, B. T., & Khosravi, K.
841 (2017). A novel hybrid artificial intelligence approach for flood susceptibility
842 assessment. *Environmental modelling & software*, 95, 229-245.

843 Chen, D., Lu, X., Liu, X., & Wang, X. (2019). Measurement of the eco-environmental effects
844 of urban sprawl: Theoretical mechanism and spatiotemporal differentiation. *Ecological*
845 *Indicators*, 105, 6-15.

846 Chen, T., Zhu, L., Niu, R. Q., Trinder, C. J., Peng, L., & Lei, T. (2020). Mapping landslide
847 susceptibility at the Three Gorges Reservoir, China, using gradient boosting decision tree,
848 random forest and information value models. *Journal of Mountain Science*, 17(3), 670-685.

849 Chen, W., Shahabi, H., Zhang, S., Khosravi, K., Shirzadi, A., Chapi, K., ... & Ma, J. (2018).
850 Landslide susceptibility modeling based on gis and novel bagging-based kernel logistic
851 regression. *Applied Sciences*, 8(12), 2540.

852 Chen, Y. R., Yeh, C. H., & Yu, B. (2011). Integrated application of the analytic hierarchy
853 process and the geographic information system for flood risk assessment and flood plain
854 management in Taiwan. *Natural Hazards*, 59(3), 1261-1276.

855 Choubin, B., Moradi, E., Golshan, M., Adamowski, J., Sajedi-Hosseini, F., & Mosavi, A.
856 (2019). An ensemble prediction of flood susceptibility using multivariate discriminant analysis,
857 classification and regression trees, and support vector machines. *Science of the Total*
858 *Environment*, 651, 2087-2096.

859 CLEAR (2002) Forest Fragmentation in Connecticut: 1985–2006 Center for Land use
860 Education and Research. <http://www.clear.uconn.edu/projects/landscape/forestfrag>. Accessed
861 05 May 2015

862 Costanza, R., d'Arge, R., De Groot, R., Farber, S., Grasso, M., Hannon, B., ... & Van Den Belt,
863 M. (1997). The value of the world's ecosystem services and natural capital. *nature*, 387(6630),
864 253-260.

865 Costanza, R., De Groot, R., Sutton, P., Van der Ploeg, S., Anderson, S. J., Kubiszewski, I., ...
866 & Turner, R. K. (2014). Changes in the global value of ecosystem services. *Global*
867 *environmental change*, 26, 152-158.

868 Dalu, T., Wasserman, R. J., Magoro, M. L., Froneman, P. W., & Weyl, O. L. (2019). River
869 nutrient water and sediment measurements inform on nutrient retention, with implications for
870 eutrophication. *Science of The Total Environment*, 684, 296-302.

871 Das, A., & Basu, T. (2020). Assessment of peri-urban wetland ecological degradation through
872 importance-performance analysis (IPA): A study on Chatra Wetland, India. *Ecological*
873 *Indicators*, 114, 106274.

874 Das, S., Pradhan, B., Shit, P. K., & Alamri, A. M. (2020). Assessment of wetland ecosystem
875 health using the pressure–State–Response (PSR) model: A case study of Mursidabad District
876 of West Bengal (India). *Sustainability*, 12(15), 5932.

877 Debanshi, S., & Pal, S. (2020a). Effects of water richness and seasonality on atmospheric
878 methane emission from the wetlands of deltaic environment. *Ecological Indicators*, 118,
879 106767.

880 Debanshi, S., & Pal, S. (2020b). Modelling water richness and habitat suitability of the
881 wetlands and measuring their spatial linkages in mature Ganges delta of India. *Journal of*
882 *Environmental Management*, 271, 110956.

883 Donchyts, G., Baart, F., Winsemius, H., Gorelick, N., Kwadijk, J., & Van De Giesen, N.
884 (2016). Earth's surface water change over the past 30 years. *Nature Climate Change*, 6(9), 810-
885 813.

886 Donner, S. (2003). The impact of cropland cover on river nutrient levels in the Mississippi
887 River Basin. *Global Ecology and Biogeography*, 12(4), 341-355.

888 Dou, J., Yamagishi, H., Pourghasemi, H. R., Yunus, A. P., Song, X., Xu, Y., & Zhu, Z. (2015).
889 An integrated artificial neural network model for the landslide susceptibility assessment of
890 Osado Island, Japan. *Natural Hazards*, 78(3), 1749-1776.

891 Dou, J., Yunus, A. P., Bui, D. T., Merghadi, A., Sahana, M., Zhu, Z., ... & Pham, B. T. (2019).
892 Assessment of advanced random forest and decision tree algorithms for modeling rainfall-
893 induced landslide susceptibility in the Izu-Oshima Volcanic Island, Japan. *Science of the Total*
894 *Environment*, 662, 332-346.

895 Dtissibe, F. Y., Ari, A. A. A., Titouna, C., Thiare, O., & Gueroui, A. M. (2020). Flood
896 forecasting based on an artificial neural network scheme. *Natural Hazards*, 104(2), 1211-1237.

897 Du, J., Song, K., & Yan, B. (2019). Impact of the Zhalong Wetland on Neighboring Land
898 Surface Temperature Based on Remote Sensing and GIS. *Chinese Geographical*
899 *Science*, 29(5), 798-808.

900 Efron, B., & Tibshirani, R. J. (1995). *Cross-validation and the bootstrap: Estimating the error*
901 *rate of a prediction rule*. Division of Biostatistics, Stanford University.

902 Finlayson, C. M. (2016). Wetland types and distribution. In 'The Wetland Book 2. Distribution,
903 Description and Conservation. (Eds CM Finlayson, GR Milton, C. Crawford, and NC
904 Davidson.) pp. 19–35.

905 Fisher, B., Turner, R. K., & Morling, P. (2009). Defining and classifying ecosystem services
906 for decision making. *Ecological economics*, 68(3), 643-653.

907 Friedman, M. (1937). The use of ranks to avoid the assumption of normality implicit in the
908 analysis of variance. *Journal of the american statistical association*, 32(200), 675-701.

909 Galib, S. M., Lucas, M. C., Chaki, N., Fahad, F. H., & Mohsin, A. B. M. (2018). Is current
910 floodplain management a cause for concern for fish and bird conservation in Bangladesh's
911 largest wetland?. *Aquatic Conservation: Marine and Freshwater Ecosystems*, 28(1), 98-114.

912 Garosi, Y., Sheklabadi, M., Pourghasemi, H. R., Besalatpour, A. A., Conoscenti, C., & Van
913 Oost, K. (2018). Comparison of differences in resolution and sources of controlling factors for
914 gully erosion susceptibility mapping. *Geoderma*, 330, 65-78.

915 Ghosh, D., Mandal, M., Banerjee, M., & Karmakar, M. (2020). Impact of hydro-geological
916 environment on availability of groundwater using analytical hierarchy process (AHP) and
917 geospatial techniques: A study from the upper Kangsabati river basin. *Groundwater for*
918 *Sustainable Development*, 11, 100419.

919 Ghosh, S., Dinda, S., Chatterjee, N. D., & Das, K. (2018). Analyzing risk factors for shrinkage
 920 and transformation of East Kolkata Wetland, India. *Spatial Information Research*, 26(6), 661-
 921 677.

922 Graf, W. L. (2006). Downstream hydrologic and geomorphic effects of large dams on
 923 American rivers. *Geomorphology*, 79(3-4), 336-360.

924 Gren, M., Groth, K. H., & Sylvén, M. (1995). Economic values of Danube floodplains. *Journal*
 925 *of Environmental Management*, 45(4), 333-345.

926 Han, T., Siddique, A., Khayat, K., Huang, J., & Kumar, A. (2020). An ensemble machine
 927 learning approach for prediction and optimization of modulus of elasticity of recycled
 928 aggregate concrete. *Construction and Building Materials*, 244, 118271.

929 He, J., Pan, Z., Liu, D., & Guo, X. (2019). Exploring the regional differences of ecosystem
 930 health and its driving factors in China. *Science of the total environment*, 673, 553-564.

931 Hesse, C., Krysanova, V., Pätzolt, J., & Hattermann, F. F. (2008). Eco-hydrological modelling
 932 in a highly regulated lowland catchment to find measures for improving water
 933 quality. *Ecological Modelling*, 218(1-2), 135-148.

934 Ho, T. K. (1998). The random subspace method for constructing decision forests. *IEEE*
 935 *transactions on pattern analysis and machine intelligence*, 20(8), 832-844.

936 Hong, H., Liu, J., Bui, D. T., Pradhan, B., Acharya, T. D., Pham, B. T., ... & Ahmad, B. B.
 937 (2018). Landslide susceptibility mapping using J48 Decision Tree with AdaBoost, Bagging
 938 and Rotation Forest ensembles in the Guangchang area (China). *Catena*, 163, 399-413.

939 Hosseinalizadeh, M., Kariminejad, N., Chen, W., Pourghasemi, H. R., Alinejad, M.,
 940 Behbahani, A. M., & Tiefenbacher, J. P. (2019). Spatial modelling of gully headcuts using
 941 UAV data and four best-first decision classifier ensembles (BFTree, Bag-BFTree, RS-BFTree,
 942 and RF-BFTree). *Geomorphology*, 329, 184-193.

943 Hu, X., & Xu, H. (2018). A new remote sensing index for assessing the spatial heterogeneity
 944 in urban ecological quality: A case from Fuzhou City, China. *Ecological Indicators*, 89, 11-21.

945 Islam, A. R. M. T., Talukdar, S., Mahato, S., Kundu, S., Eibek, K. U., Pham, Q. B., ... & Linh,
 946 N. T. T. (2020). Flood susceptibility modelling using advanced ensemble machine learning
 947 models. *Geoscience Frontiers*.

948 Jiang, W. G., Li, J., Li, J. H., Xie, Z. R., & Wang, W. J. (2005). Assessment of wetland
949 ecosystem health in the Liaohe River Delta. *Acta ecologica sinica*, 25(3), 408-414.

950 Jones, A. S., Stevens, D. K., Horsburgh, J. S., & Mesner, N. O. (2011). Surrogate Measures for
951 Providing High Frequency Estimates of Total Suspended Solids and Total Phosphorus
952 Concentrations 1. *JAWRA Journal of the American Water Resources Association*, 47(2), 239-
953 253

954 Junk, W. J., An, S., Finlayson, C. M., Gopal, B., Květ, J., Mitchell, S. A., ... & Robarts, R. D.
955 (2013). Current state of knowledge regarding the world's wetlands and their future under global
956 climate change: a synthesis. *Aquatic sciences*, 75(1), 151-167.

957 Keddy, P., Gaudet, C., & Fraser, L. H. (2000). Effects of low and high nutrients on the
958 competitive hierarchy of 26 shoreline plants. *Journal of Ecology*, 413-423.

959 Khatun, R., Talukdar, S., Pal, S., & Kundu, S. (2021). Measuring dam induced alteration in
960 water richness and eco-hydrological deficit in flood plain wetland. *Journal of Environmental*
961 *Management*, 285, 112157.

962 Knorn, J., Rabe, A., Radeloff, V. C., Kuemmerle, T., Kozak, J., & Hostert, P. (2009). Land
963 cover mapping of large areas using chain classification of neighboring Landsat satellite
964 images. *Remote Sensing of Environment*, 113(5), 957-964.

965 Kopperoinen, L., Itkonen, P., & Niemelä, J. (2014). Using expert knowledge in combining
966 green infrastructure and ecosystem services in land use planning: an insight into a new place-
967 based methodology. *Landscape ecology*, 29(8), 1361-1375.

968 Koschke, L., Fürst, C., Frank, S., & Makeschin, F. (2012). A multi-criteria approach for an
969 integrated land-cover-based assessment of ecosystem services provision to support landscape
970 planning. *Ecological indicators*, 21, 54-66.

971 Kumar, S., & Deswal, S. (2020). Estimation of phosphorus reduction from wastewater by
972 artificial neural network, random forest and M5P model tree approaches. *Pollution*, 6(2), 417-
973 428.

974 Lacaux, J. P., Tourre, Y. M., Vignolles, C., Ndione, J. A., & Lafaye, M. (2007). Classification
975 of ponds from high-spatial resolution remote sensing: Application to Rift Valley Fever
976 epidemics in Senegal. *Remote Sensing of Environment*, 106(1), 66-74.

977 Lai, T. Y., Salminen, J., Jäppinen, J. P., Koljonen, S., Mononen, L., Nieminen, E., ... &
978 Oinonen, S. (2018). Bridging the gap between ecosystem service indicators and ecosystem
979 accounting in Finland. *Ecological modelling*, 377, 51-65.

980 Lantz, S. M., Gawlik, D. E., & Cook, M. I. (2011). The effects of water depth and emergent
981 vegetation on foraging success and habitat selection of wading birds in the
982 Everglades. *Waterbirds*, 34(4), 439-447.

983 LEDDA, A., MONTIS, A. D., & SERRA, V. (2019). THE EFFECT OF BUILDINGS ON
984 LANDSCAPE FRAGMENTATION IN NATURA 2000 SITES. *Federico II Open Access*
985 *University Press*.

986 Lee, S., Kim, J. C., Jung, H. S., Lee, M. J., & Lee, S. (2017). Spatial prediction of flood
987 susceptibility using random-forest and boosted-tree models in Seoul metropolitan city,
988 Korea. *Geomatics, Natural Hazards and Risk*, 8(2), 1185-1203.

989 Li, Y., Wu, L., Han, Q., Wang, X., Zou, T., & Fan, C. (2021). Estimation of remote sensing
990 based ecological index along the Grand Canal based on PCA-AHP-TOPSIS
991 methodology. *Ecological Indicators*, 122, 107214.

992 Liao, C., Yue, Y., Wang, K., Fensholt, R., Tong, X., & Brandt, M. (2018). Ecological
993 restoration enhances ecosystem health in the karst regions of southwest China. *Ecological*
994 *Indicators*, 90, 416-425.

995 Lin, Q., Zhang, K., Shen, J., & Liu, E. (2019). Integrating long-term dynamics of ecosystem
996 services into restoration and management of large shallow lakes. *Science of the Total*
997 *Environment*, 671, 66-75.

998 Luo, Q., Zhang, X., Li, Z., Yang, M., & Lin, Y. (2018). The effects of China's Ecological
999 Control Line policy on ecosystem services: The case of Wuhan City. *Ecological Indicators*, 93,
1000 292-301.

1001 MA (Millennium Ecosystem Assessment), 2005. Ecosystems and Human Well-being:
1002 Synthesis. Island Press/World Resources Institute, Washington, DC.

1003 Mai, S., Xu, S., & Pan, Y. (2005). Application of the PSR model to the evaluation of wetland
1004 ecosystem health. *Tropical Geography*, 25(4), 317.

1005 Maxwell, A. E., Warner, T. A., & Fang, F. (2018). Implementation of machine-learning
1006 classification in remote sensing: An applied review. *International Journal of Remote*
1007 *Sensing*, 39(9), 2784-2817.

1008 Mitsch, W. J. (2010). Conservation, restoration and creation of wetlands: a global
1009 perspective. *Ecological Restoration: A Global Challenge*. Cambridge University Press,
1010 Cambridge, 175-188.

1011 Montoya-Tangarife, Claudia, et al. "Monitoring the effects of land cover change on the supply
1012 of ecosystem services in an urban region: A study of Santiago-Valparaíso, Chile." *PloS*
1013 *one* 12.11 (2017): e0188117.

1014 Mukherjee, K., & Pal, S. (2021). Hydrological and landscape dynamics of floodplain wetlands
1015 of the Diara region, Eastern India. *Ecological Indicators*, 121, 106961

1016 Mukul, S. A., Sohel, M. S. I., Herbohn, J., Inostroza, L., & König, H. (2017). Integrating
1017 ecosystem services supply potential from future land-use scenarios in protected area
1018 management: A Bangladesh case study. *Ecosystem Services*, 26, 355-364.

1019 Mulder, V. L., De Bruin, S., Schaepman, M. E., & Mayr, T. R. (2011). The use of remote
1020 sensing in soil and terrain mapping—A review. *Geoderma*, 162(1-2), 1-19.

1021 Muro, J., Strauch, A., Heinemann, S., Steinbach, S., Thonfeld, F., Waske, B., & Diekkrüger,
1022 B. (2018). Land surface temperature trends as indicator of land use changes in
1023 wetlands. *International journal of applied earth observation and geoinformation*, 70, 62-71.

1024 Nasirian, H., & Salehzadeh, A. (2019). Effect of seasonality on the population density of
1025 wetland aquatic insects: A case study of the Hawr Al Azim and Shadegan wetlands,
1026 Iran. *Veterinary world*, 12(4), 584.

1027 Nayak, P., Behera, P., Behera, D., & Rani, D. (2020). Estimation of the species diversity and
1028 evenness in mango under coastal Odisha climatic conditions. *Journal of Pharmacognosy and*
1029 *Phytochemistry*, 9(3), 756-758.

1030 Neri, A. C., Dupin, P., & Sánchez, L. E. (2016). A pressure–state–response approach to
1031 cumulative impact assessment. *Journal of Cleaner Production*, 126, 288-298.

1032 Nhu, V. H., Janizadeh, S., Avand, M., Chen, W., Farzin, M., Omidvar, E., ... & Lee, S. (2020).
1033 Gis-based gully erosion susceptibility mapping: A comparison of computational ensemble data
1034 mining models. *Applied Sciences*, 10(6), 2039.

1035 Ning, Y.; Zhao, W.; Li, B.; Zhang, P. Land Use Ecological Security Analysis in Baoding City
1036 Based on Improved Ecological Footprint Model.

1037 Nohani, E., Moharrami, M., Sharafi, S., Khosravi, K., Pradhan, B., Pham, B. T., ... & M
1038 Melesse, A. (2019). Landslide susceptibility mapping using different GIS-based bivariate
1039 models. *Water*, 11(7), 1402.

1040 Olson, K. R., Al-Kaisi, M., Lal, R., & Morton, L. W. (2017). Soil ecosystem services and
1041 intensified cropping systems. *Journal of Soil and Water Conservation*, 72(3), 64A-69A.

1042 Onan, A. (2016). Classifier and feature set ensembles for web page classification. *Journal of*
1043 *Information Science*, 42(2), 150-165.

1044 Pal, S., & Sarda, R. (2020). Damming effects on the degree of hydrological alteration and
1045 stability of wetland in lower Atreyee River basin. *Ecological Indicators*, 116, 106542.

1046 Pal, S., & Talukdar, S. (2018). Application of frequency ratio and logistic regression models
1047 for assessing physical wetland vulnerability in Punarbhaba river basin of Indo-
1048 Bangladesh. *Human and Ecological Risk Assessment: An International Journal*, 24(5), 1291-
1049 1311.

1050 Pal, S., & Talukdar, S. (2018). Drivers of vulnerability to wetlands in Punarbhaba river basin
1051 of India-Bangladesh. *Ecological Indicators*, 93, 612-626.

1052 Pal, S., & Talukdar, S. (2020). Assessing the role of hydrological modifications on land
1053 use/land cover dynamics in Punarbhaba river basin of Indo-Bangladesh. *Environment,*
1054 *Development and Sustainability*, 22(1), 363-382.

1055 Pal, S., & Ziaul, S. K. (2017). Detection of land use and land cover change and land surface
1056 temperature in English Bazar urban centre. *The Egyptian Journal of Remote Sensing and Space*
1057 *Science*, 20(1), 125-145.

1058 Pal, S., Saha, A., & Das, T. (2019). Analysis of flow modifications and stress in the Tangon
1059 river basin of the Barind tract. *International Journal of River Basin Management*, 17(3), 301-
1060 321.

1061 Pal, S., Singha, P., Lepcha, K., Debanshi, S., Talukdar, S., & Saha, T. K. (2021). Proposing
1062 multicriteria decision based valuation of ecosystem services for fragmented landscape in
1063 mountainous environment. *Remote Sensing Applications: Society and Environment*, 21,
1064 100454.

1065 Pal, S., Talukdar, S., & Ghosh, R. (2020). Damming effect on habitat quality of riparian
1066 corridor. *Ecological Indicators*, 114, 106300.

1067 Park, T., Chen, C., Macias-Fauria, M., Tømmervik, H., Choi, S., Winkler, A., ... & Myneni, R.
1068 B. (2019). Changes in timing of seasonal peak photosynthetic activity in northern
1069 ecosystems. *Global change biology*, 25(7), 2382-2395.

1070 Pham, B. T., Bui, D. T., & Prakash, I. (2018). Bagging based support vector machines for
1071 spatial prediction of landslides. *Environmental earth sciences*, 77(4), 146

1072 Pham, B. T., Bui, D. T., Prakash, I., & Dholakia, M. B. (2017). Hybrid integration of Multilayer
1073 Perceptron Neural Networks and machine learning ensembles for landslide susceptibility
1074 assessment at Himalayan area (India) using GIS. *Catena*, 149, 52-63.

1075 Piao, Y., Piao, M., Jin, C. H., Shon, H. S., Chung, J. M., Hwang, B., & Ryu, K. H. (2015). A
1076 new ensemble method with feature space partitioning for high-dimensional data
1077 classification. *Mathematical Problems in Engineering*, 2015.

1078 Prasad, A. M., Iverson, L. R., & Liaw, A. (2006). Newer classification and regression tree
1079 techniques: bagging and random forests for ecological prediction. *Ecosystems*, 9(2), 181-199.

1080 Pritchard, R., Grundy, I. M., van der Horst, D., & Ryan, C. M. (2019). Environmental incomes
1081 sustained as provisioning ecosystem service availability declines along a woodland resource
1082 gradient in Zimbabwe. *World Development*, 122, 325-338.

1083 Quinlan, J. R. (1987). Simplifying decision trees. *International journal of man-machine*
1084 *studies*, 27(3), 221-234.

1085 Quinlan, J. R. (1992, November). Learning with continuous classes. In *5th Australian joint*
1086 *conference on artificial intelligence* (Vol. 92, pp. 343-348).

1087 Quyen, N. T. K., Berg, H., Gallardo, W., & Da, C. T. (2017). Stakeholders' perceptions of
1088 ecosystem services and Pangasius catfish farming development along the Hau River in the
1089 Mekong Delta, Vietnam. *Ecosystem services*, 25, 2-14.

1090 Ramsar, C.O.P., 2002, November. Wetlands: water, life, and culture. In: Report of 8th meeting
1091 of the conference of the contracting parties to the Convention on Wetlands (Ramsar, Iran,
1092 1971), Spain, pp. 18–26.

1093 Richter, B., Baumgartner, J., Wigington, R., & Braun, D. (1997). How much water does a river
1094 need?. *Freshwater biology*, 37(1), 231-249.

1095 Sachdeva, S., Bhatia, T., & Verma, A. K. (2017, July). Flood susceptibility mapping using
1096 GIS-based support vector machine and particle swarm optimization: A case study in
1097 Uttarakhand (India). In *2017 8th International conference on computing, communication and*
1098 *networking technologies (ICCCNT)* (pp. 1-7). IEEE.

1099 Saha, S., Saha, A., Hembram, T. K., Pradhan, B., & Alamri, A. M. (2020). Evaluating the
1100 performance of individual and novel ensemble of machine learning and statistical models for
1101 landslide susceptibility assessment at Rudraprayag District of Garhwal Himalaya. *Applied*
1102 *Sciences*, 10(11), 3772.

1103 Saha, S., Saha, M., Mukherjee, K., Arabameri, A., Ngo, P. T. T., & Paul, G. C. (2020).
1104 Predicting the deforestation probability using the binary logistic regression, random forest,
1105 ensemble rotational forest, REPTree: A case study at the Gumani River Basin, India. *Science*
1106 *of The Total Environment*, 730, 139197.

1107 Saha, T. K., & Pal, S. (2019). Emerging conflict between agriculture extension and physical
1108 existence of wetland in post-dam period in Atreyee River basin of Indo-
1109 Bangladesh. *Environment, Development and Sustainability*, 21(3), 1485-1505.

1110 Saha, T. K., & Pal, S. (2019). Exploring physical wetland vulnerability of Atreyee river basin
1111 in India and Bangladesh using logistic regression and fuzzy logic approaches. *Ecological*
1112 *indicators*, 98, 251-265.

1113 Sahana, M., Rehman, S., Sajjad, H., & Hong, H. (2020). Exploring effectiveness of frequency
1114 ratio and support vector machine models in storm surge flood susceptibility assessment: A
1115 study of Sundarban Biosphere Reserve, India. *Catena*, 189, 104450.

1116 Schmidt, T. S., Battke, B., Grosspietsch, D., & Hoffmann, V. H. (2016). Do deployment
1117 policies pick technologies by (not) picking applications?—A simulation of investment
1118 decisions in technologies with multiple applications. *Research Policy*, 45(10), 1965-1983.

1119 Secchi, B. (1864). *La fanciulla delle Asturie: tragedia lirica in 4 atti: da rappresentarsi nel*
1120 *Teatro di Apollo, carnevale 1865*.

1121 Shahabi, H., Shirzadi, A., Ghaderi, K., Omidvar, E., Al-Ansari, N., Clague, J. J., ... & Rahmati,
1122 O. (2020). Flood detection and susceptibility mapping using sentinel-1 remote sensing data and

1123 a machine learning approach: Hybrid intelligence of bagging ensemble based on k-nearest
 1124 neighbor classifier. *Remote Sensing*, 12(2), 266.

1125 Shannon, C. E., & Weaver, W. (1949). The mathematical theory of information. *Urbana:*
 1126 *University of Illinois Press*, 97.

1127 Shen, X., Sun, T., Su, M., Dang, Z., & Yang, Z. (2019). Short-term response of aquatic
 1128 ecosystem metabolism to turbidity disturbance in experimental estuarine wetlands. *Ecological*
 1129 *Engineering*, 136, 55-61.

1130 Singha, P., Das, P., Talukdar, S., & Pal, S. (2020). Modeling livelihood vulnerability in erosion
 1131 and flooding induced river island in Ganges riparian corridor, India. *Ecological*
 1132 *Indicators*, 119, 106825.

1133 Solomatine, D. P., & Dulal, K. N. (2003). Model trees as an alternative to neural networks in
 1134 rainfall—runoff modelling. *Hydrological Sciences Journal*, 48(3), 399-411.

1135 Sun, B., Tang, J., Yu, D., Song, Z., & Wang, P. (2019). Ecosystem health assessment: A PSR
 1136 analysis combining AHP and FCE methods for Jiaozhou Bay, China1. *Ocean & Coastal*
 1137 *Management*, 168, 41-50.

1138 Sun, T., Lin, W., Chen, G., Guo, P., & Zeng, Y. (2016). Wetland ecosystem health assessment
 1139 through integrating remote sensing and inventory data with an assessment model for the
 1140 Hangzhou Bay, China. *Science of the Total Environment*, 566, 627-640.

1141 Svozil, D., Kvasnicka, V., & Pospichal, J. (1997). Introduction to multi-layer feed-forward
 1142 neural networks. *Chemometrics and intelligent laboratory systems*, 39(1), 43-62.

1143 Tabbussum, R., & Dar, A. Q. (2021). Performance evaluation of artificial intelligence
 1144 paradigms—artificial neural networks, fuzzy logic, and adaptive neuro-fuzzy inference system
 1145 for flood prediction. *Environmental Science and Pollution Research*, 1-18.

1146 Talukdar, S., & Pal, S. (2017). Impact of dam on inundation regime of flood plain wetland of
 1147 punarbhaba river basin of barind tract of Indo-Bangladesh. *International Soil and Water*
 1148 *Conservation Research*, 5(2), 109-121.

1149 Talukdar, S., & Pal, S. (2019). Effects of damming on the hydrological regime of Punarbhaba
 1150 river basin wetlands. *Ecological Engineering*, 135, 61-74.

1151 Talukdar, S., & Pal, S. (2020a). Modeling flood plain wetland transformation in consequences
1152 of flow alteration in Punarbhaba river in India and Bangladesh. *Journal of Cleaner*
1153 *Production*, 261, 120767.

1154 Talukdar, S., & Pal, S. (2020b). Wetland habitat vulnerability of lower Punarbhaba river basin
1155 of the uplifted Barind region of Indo-Bangladesh. *Geocarto International*, 35(8), 857-886.

1156 Talukdar, S., Pal, S., & Singha, P. (2021). Proposing artificial intelligence based livelihood
1157 vulnerability index in river islands. *Journal of Cleaner Production*, 284, 124707.

1158 Talukdar, S., Pal, S., Chakraborty, A., & Mahato, S. (2020a). Damming effects on trophic and
1159 habitat state of riparian wetlands and their spatial relationship. *Ecological Indicators*, 118,
1160 106757.

1161 Tehrany, M. S., Pradhan, B., Mansor, S., & Ahmad, N. (2015). Flood susceptibility assessment
1162 using GIS-based support vector machine model with different kernel types. *Catena*, 125, 91-
1163 101.

1164 Tien Bui, D., Pradhan, B., Lofman, O., & Revhaug, I. (2012). Landslide susceptibility
1165 assessment in vietnam using support vector machines, decision tree, and Naive Bayes
1166 Models. *Mathematical problems in Engineering*, 2012.

1167 Tomaselli, V., Tenerelli, P., & Sciandrello, S. (2012). Mapping and quantifying habitat
1168 fragmentation in small coastal areas: a case study of three protected wetlands in Apulia
1169 (Italy). *Environmental monitoring and assessment*, 184(2), 693-713.

1170 Truong, X. L., Mitamura, M., Kono, Y., Raghavan, V., Yonezawa, G., Truong, X. Q., ... &
1171 Lee, S. (2018). Enhancing prediction performance of landslide susceptibility model using
1172 hybrid machine learning approach of bagging ensemble and logistic model tree. *Applied*
1173 *Sciences*, 8(7), 1046.

1174 Turner, R. E., & Rabalais, N. N. (2003). Linking landscape and water quality in the Mississippi
1175 River Basin for 200 years. *Bioscience*, 53(6), 563-572.

1176 Uhel, R., Spyropoulou, R., Breton, F., Beltrame, C., Arévalo, J., Richard, D., ... & Marin, E.
1177 (2010). Ecosystem accounting and the cost of biodiversity losses: the case of coastal
1178 Mediterranean wetlands. *European Environment Agency Copenhagen*, 20151841.

1179 Vihervaara, P., Kumpula, T., Tanskanen, A., & Burkhard, B. (2010). Ecosystem services—A
 1180 tool for sustainable management of human–environment systems. Case study Finnish Forest
 1181 Lapland. *Ecological complexity*, 7(3), 410-420.

1182 Vogel, R. M., & Fennessey, N. M. (1995). Flow duration curves II: A review of applications
 1183 in water resources planning 1. *JAWRA Journal of the American Water Resources*
 1184 *Association*, 31(6), 1029-1039.

1185 Vogt, P., Riitters, K. H., Estreguil, C., Kozak, J., Wade, T. G., & Wickham, J. D. (2007).
 1186 Mapping spatial patterns with morphological image processing. *Landscape ecology*, 22(2),
 1187 171-177.

1188 Wan, R., Wang, P., Wang, X., Yao, X., & Dai, X. (2019). Mapping aboveground biomass of
 1189 four typical vegetation types in the Poyang Lake wetlands based on random forest modelling
 1190 and landsat images. *Frontiers in plant science*, 10, 1281.

1191 Wang, X., & Tang, X. (2006). Random sampling for subspace face recognition. *International*
 1192 *Journal of Computer Vision*, 70(1), 91-104.

1193 Wang, Y., Hong, H., Chen, W., Li, S., Pamučar, D., Gigović, L., ... & Duan, H. (2019a). A
 1194 hybrid GIS multi-criteria decision-making method for flood susceptibility mapping at
 1195 Shangyou, China. *Remote Sensing*, 11(1), 62.

1196 Wang, Z., Yang, L., Yin, J., & Zhang, B. (2018). Assessment and prediction of environmental
 1197 sustainability in China based on a modified ecological footprint model. *Resources*,
 1198 *Conservation and Recycling*, 132, 301-313.

1199 Wernand, M. R. (2010). On the history of the Secchi disc. *Journal of the European Optical*
 1200 *Society-Rapid Publications*, 5.

1201 Wetzel, R. G. (2001). *Limnology: lake and river ecosystems*. gulf professional publishing.

1202 Wondie, A. (2018). Ecological conditions and ecosystem services of wetlands in the Lake Tana
 1203 Area, Ethiopia. *Ecohydrology & Hydrobiology*, 18(2), 231-244.

1204 Wu, H., Kimball, J. S., Zhou, N., Alfieri, L., Luo, L., Du, J., & Huang, Z. (2019). Evaluation
 1205 of real-time global flood modeling with satellite surface inundation observations from
 1206 SMAP. *Remote Sensing of Environment*, 233, 111360.

- 1207 Wu, J., Wang, X., Zhong, B., Yang, A., Jue, K., Wu, J., ... & Liu, Q. (2020). Ecological
1208 environment assessment for Greater Mekong Subregion based on Pressure-State-Response
1209 framework by remote sensing. *Ecological Indicators*, 117, 106521.
- 1210 Yaman, M. A., Subasi, A., & Rattay, F. (2018). Comparison of random subspace and voting
1211 ensemble machine learning methods for face recognition. *Symmetry*, 10(11), 651.
- 1212 Yang, F., Su, R., Jian, H., & Yao, Q. (2016). Using algal biomass to evaluate numeric nutrient
1213 criteria in an estuary: A case study of Daliaohe Estuary in China. *Ecological Indicators*, 70,
1214 373-381.
- 1215 Zhang, F., Wang, L., & Su, W. (2016). Evaluation of land ecological security in Chongqing
1216 based on the matter-element analysis-DPSIR model. *China Environmental Science*, 36(10),
1217 3126-3134.
- 1218 Zhang, L., Zhao, J., Yang, H., Shi, W., Miao, Y., He, F., ... & Jiang, Z. (2019, March).
1219 Multiclass vertebral fracture classification using ensemble probability SVM with multi-feature
1220 selection. In *Medical Imaging 2019: Computer-Aided Diagnosis* (Vol. 10950, p. 1095025).
1221 International Society for Optics and Photonics.
- 1222 Zhao, G., Pang, B., Xu, Z., Peng, D., & Xu, L. (2019). Assessment of urban flood susceptibility
1223 using semi-supervised machine learning model. *Science of The Total Environment*, 659, 940-
1224 949.
- 1225 Zhu, A., Yang, Z., Liang, Z., Gao, L., Li, R., Hou, L., ... & Cao, L. (2020). Integrating
1226 hydrochemical and biological approaches to investigate the surface water and groundwater
1227 interactions in the hyporheic zone of the Liuxi River basin, southern China. *Journal of*
1228 *Hydrology*, 583, 124622.
- 1229 Zorrilla-Miras, P., Palomo, I., Gómez-Baggethun, E., Martín-López, B., Lomas, P. L., &
1230 Montes, C. (2014). Effects of land-use change on wetland ecosystem services: A case study in
1231 the Doñana marshes (SW Spain). *Landscape and Urban Planning*, 122, 160-174.